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Climate change impacts and adaptation strategies for a hydro-dominated power system via stochastic optimization

Omar J. Guerra[a,1], Diego A. Tejada[b], Gintaras V. Reklaitis[a,*]

[a] School of Chemical Engineering, Purdue University, West Lafayette, IN 47907, USA
[b] Institute for Research in Technology (IIT), Pontifical Comillas University, Santa Cruz de Marcenado 26, 28015 Madrid, Spain

HIGHLIGHTS

- Climate change impacts on a hydro-dominated power system are evaluated.
- Key uncertain parameters are identified using global sensitivity analysis.
- A two-stage stochastic approach for power system design and planning is developed.
- Climate change will reduce the capacity factor of hydropower plants in Colombia.
- Climate change will increase natural gas demand in the Colombian power sector.

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ABSTRACT

As outlined in the Paris Agreement on climate change, efforts to mitigate and adapt to climate change will require new modes of development of the energy sector including the transformation and expansion of power systems to low-carbon and more resilient designs. However, there is a need for more systematic tools to support decision-making processes in the context of climate change impacts and adaptation strategies for the energy and power sectors. For instance, quantitative approaches should be developed and implemented for the assessment of the impacts and hedging strategies associated with the uncertainties inherent to energy and power planning problems. This study addresses the development and implementation of an integrated model-based system analysis, which uses general circulation models, global sensitivity analysis, and stochastic optimization techniques, for the optimal design and planning of the Colombian power system in view of submitted climate pledges and climate change adaptation. It was found that during the 2015 to 2029 time frame, climate change will likely reduce the capacity factor of hydropower generation by 5.5–17.1%. Additionally, it was established that the independent effects of three key uncertain parameters, i.e., capacity factor of hydropower generation, gas prices, and emission reduction target, account for ~96% of the variance in the total cost for the required expansion and operation of the power system. Furthermore, when uncertainty is taken into account, the optimal expansion strategy consists of rescheduling of investments in hydropower plants and investing more in carbon management technologies and renewable power plants to compensate for the uncertainty in hydropower generation, climate policy, and gas prices.

1. Introduction

1.1. Electricity demand, CO_2 emissions, and climate change

Global gross electricity production increased, on average, 3.4% per year in the four decades from 1974 to 2014, according to the International Energy Agency [1]. Despite recent advancements in the deployment of renewable energy sources, the power sector still relies overwhelmingly on electricity generation from fossil fuels, mainly coal and natural gas. For instance, in 2014 roughly 66.7% of the global electricity production, i.e. 23,815 TWh, was from power plants that used fossil fuels. In particular, in 2014 the share of fossil fuels in the electricity mix was 40.8%, 21.6%, and 4.3% for coal, natural gas, and oil, respectively. Hydroelectric and nuclear power plants supplied

* Corresponding author.
E-mail addresses: oguerra@purdue.edu, OmarJose.GuerraFernandez@nrel.gov (O.J. Guerra), diego.tejada@iit.comillas.edu (D.A. Tejada), reklaiti@purdue.edu (G.V. Reklaitis).
[1] Now at National Renewable Energy Laboratory (NREL), Golden, CO 80401, USA.

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Nomenclature

Indices

h	hydropower plants in the power system
i, j	indices for uncertain parameters evaluated in the global sensitivity analysis
t	time period, i.e., year

Parameters and variables

α_h	average ratio between the average capacity factor and the capacity factor of hydropower plant h
$AvCF_t$	average capacity factor during year t
$AvPr_t$	normalized annual average precipitation during year t
$AvTe_t$	normalized annual average ambient temperature during year t
$CF_{h,t}$	capacity factor of hydropower plant h during year t
P_i, P_j	uncertaint parameters in the global sensitivy analysis
S_i	first-order sensitivity index for uncertain parameter i
$S_{i,j}$	second-order sensitivity index associated with uncertain parameter i and j
ST_i	total sensitivity index for uncertain parameter i
$V(E(Z/P_i))$	variance of the expected value of output variable Z given parameter P_i
$V(E(Z/P_i, P_j))$	the variance of the expected value of output variable Z given parameters P_i and P_j
$V(Z)$	total variance of the output variable Z, e.g., total cost associated with the expansion and operation of the power system
Z^{ws}	total cost obtained from the *wait-and-see* approach
Z^d	expected total cost using the expected value solution
Z^*	total cost associated with the stochastic formulation
$EVPI$	expected value of perfect information
VSS	value of the stochastic solution

16.4% and 10.6%, respectively. Additionally, geothermal, solar, wind, and tidal power generation provided about 4.2%, while biofuels and waste based power made up the remaining 2.1% [1]. In spite of the increase in electricity supply in recent decades, severe deprivation in electricity continues, with ~1.2 billion people without access to electricity [2]. Furthermore, it is expected that electricity demand will increase between 47.8% and 80.2% from 2014 to 2040 [2].

However, efforts to increase electricity supply are impacted by the reality that currently, about 42% of the world's energy-related CO_2 emissions in 2013 were from the power sector [3]. Moreover, the power sector accounted for roughly 90% of the total water withdrawals by the energy sector in 2010 [4]. Thus, given this reality, electric power systems face two important challenges associated, either directly or indirectly, with climate change, that is, the statistically significant change in the mean condition of the climate or in its variability, enduring for an extended time period, e.g., decades or longer, (https://www.ipcc.ch/ipccreports/tar/wg1/518.htm). The first challenge arises from the pledges made by each country during the 2015 United Nations Climate Change Conference in Paris (COP21) that require reductions in CO_2 emissions from the power sector. These reductions can be achieved by a combination of different alternatives, including integration of renewable resources, retrofitting of fossil power plants with carbon capture and sequestration (CCS) and carbon capture and utilization (CCU) technologies, and the enforcement of demand-side management (DSM) policies either to reduce electricity demand or to shift load to periods when variable renewable resources are more available [5–7]. Second challenge arises from the intensification of climate and weather variability, including rainfall shifts in tropical regions [8,9] and increase in the occurrence of La Niña and El Niño abnormal weather patterns [10,11], that will likely affect the availability of water resources used for hydropower generation and the temperature of fresh water for cooling in thermoelectric power plants [12,13]. The impacts of these abnormal weather patterns on hydropower generation are more intensive in Central America, Northwest United States, South America, Southeast Asia, Southeast Australia, and Iberia [14]. Furthermore, in the power sector, large CO_2 emission reduction targets are expected to increase the demand of water for electricity production [15], which will aggravate the vulnerability of power systems to climate change. Therefore, the design and planning of power systems for climate change adaptation are becoming increasingly important issues [16–18]. This paper seeks to show that integrated model-based system analyses [17,19,20] can provide insights regarding the following key questions:

1. What is the quantitative impact of variability of water availability on power systems?
2. What is the most cost-efficient path to cleaner, reliable, and resilient power systems, in view of climate change?, and
3. What is the most cost-effective strategy to curb CO_2 emissions, in view of COP21 pledges?

1.2. Hydro-dominated power systems: Climate change impacts and stochastic programming

A number of studies have sought to provide assessments of the impact of climate change on the power sector [21–23] as well as the corresponding policy implications [24–26]. These studies focused mostly on nuclear, gas, and coal power plants [21,24,27]. Moreover, based on emission scenarios and general circulation models (GCMs), declines in usable generation capacity of up to 74% and 86% of worldwide hydroelectric and thermoelectric power plants were projected during the 2040–2069 time frame, respectively [28]. Therefore, besides the well documented effects on thermal power generation, climate change will also likely impact hydropower generation. It is noteworthy that in 2010 hydropower generation represented more than half of the total electricity generation in about 36 countries around the world, most of them developing countries [29]. Further, global gross hydropower potential is estimated to range from 52 PWh/year to 128 PWh/year [30,31], while global exploitable potential is estimated to range from 6 PWh/year to 18 PWh/year [31]. In Colombia, gross and exploitable hydropower potentials are estimated to be approximately 1641 TWh/year [30] and 518 TWh/year [31], respectively. The effects of climate change on hydropower generation have been evaluated at both local [32–34] and global [35–37] scales. Some studies have been focused on the impact of climate change on hydro-dominated power systems in developing economies in South America [38], Asia [39], and Africa [40]. It is noteworthy that, beside the impacts of climate change, the expansion of hydropower generation is also facing opposition from civil society in some developing countries, e.g., Brazil [41,42]. This opposition is driven by potential impacts of dam projects on indigenous communities and areas of high environmental sensitivity [42–44]. The ecological and social impacts associated with hydropower dams include transboundary conflicts, relocation of people, habitat changes (threatening the biodiversity of freshwater ecosystems), and free-flowing river fragmentation [45,46]. In the contest of adaptation strategies for climate change, it was found that replacement of cooling system types, increased plant efficiencies, and fuel switches are effective adaptation strategies for reducing the vulnerability of thermal power plants to climate and freshwater variability. Further, increased plant efficiencies, integrated management of reservoirs, and increased capacity of other renewable energy sources, i.e., solar, wind, and biomass power, have

been identified as additional climate change adaptation strategies for hydropower plants and hydro-dominated power systems [28,38,42].

Despite the advances in the understanding and assessment of the vulnerability of power systems to climate change, more efforts are needed in the systematic evaluation of strategies for the adaptation of hydro-dominated power systems to climate change using integrated model-based system analysis. For instance, the long-term planning of these power systems should address the challenges associated with CO_2 emission reduction and climate change adaption, e.g., adaptation to variability in the availability of water resources, while considering the uncertainties inherent to power system planning problems. These uncertainties include electricity demand [47–49], natural gas prices [48,50], water inflows for hydropower generation or power generation capacity [38,51], climate policy [52,53], as well as capital cost associated with power generation and carbon management technologies [52,54]. Indeed, stochastic programming approaches, e.g., probabilistic programming [55] and programming with recourse [56–58], as well as fuzzy mathematical programming [59] have been developed for power generation and transmission planning under uncertainty. Two-stage stochastic models can be used to evaluate optimal hedging strategies in planning problems with uncertain parameters, which provide policies for adaptation to realizations of uncertainties [54,60,61]. These types of stochastic models have been widely used by the research community to address energy [62] and power [50,52,63] planning problems. However, the development of systematic approaches for the selection of the uncertain parameters remains an important barrier, particularly for practical applications. For example, the uncertain parameters subjected to study are commonly selected a priori rather than using rigorous procedures [50,52,63].

1.3. Research aims

This study aims to: (1) implement a method for the quantification and identification of the main uncertain parameters affecting the performance of power systems, and (2) develop and implement an integrated stochastic (two-stage) framework for the optimal design and planning of hydro-dominated power systems, in view of COP21 pledges and climate change. In this work, the quantification and identification of the main uncertain parameters is based on global sensitivity analysis. Sensitivity analysis can be defined as: "*The study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input*" [64]. Then, an integrated stochastic optimization-based framework is formulated based on a deterministic power planning framework recently developed by

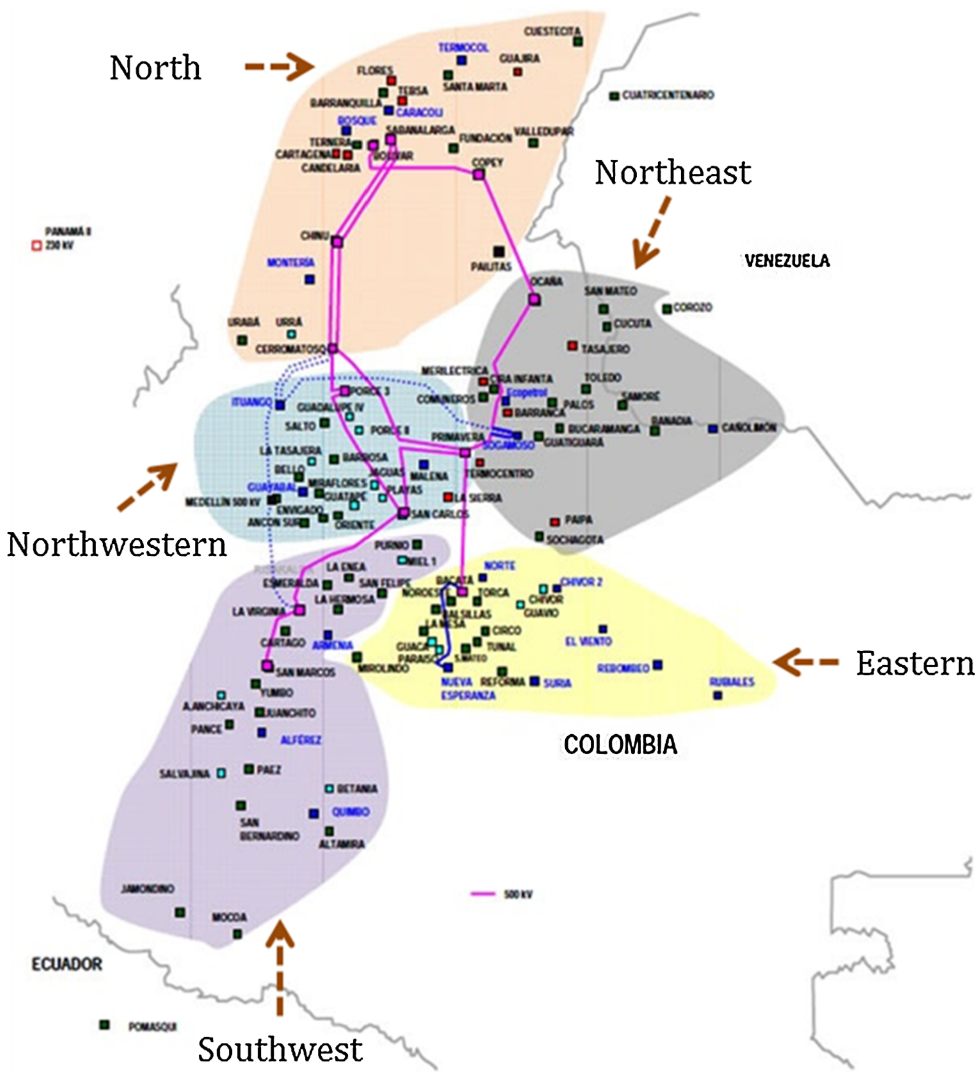

Fig. 1. Colombian interconnected power system [65]. The five colored areas represent interconnected regions. Solid pink lines denote transmission lines @ 500 kV. Pink squares represent substation sites. Red squares denote fossil (coal or natural gas) power plants. Celeste squares denote large hydropower plants. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the authors [65]. The Colombian power system was used as case study, considering a planning horizon from 2015 to 2029 (details are provided in Section 2.1). The stochastic framework addresses the integrated design and planning of power transmission and generation expansion. It considers reliability constraints (spinning and non-spinning reserves), CO_2 emission constraints in view of COP21 pledges, and mitigation strategies for CO_2 emissions (the integration of CCS technologies and renewable energy generation). The Colombian power system serves as an informative case study because hydropower plants represent ~70% of the country's total installed electricity generation capacity [65]. The advantages of the stochastic approach arise from the ability to quantitatively take into account the uncertainties inherent to these decision-making problems, including uncertainties in factors such as fuel prices, emission reduction policy, and capacity factor of hydropower plants.

2. Materials and methods

2.1. Overview of the Colombian interconnected power system

Details concerning the Colombian power system, including existing power generation and transmission assets, projected electricity demand for each interconnected region, and ongoing projects for the expansion of power generation capacity, are available from the Mining and Energy Planning Unit-UPME [66,67] and the Independent System Operator (ISO) in Colombia XM [68]. The Colombian interconnected power system, as shown in Fig. 1, consists of 5 interconnected regions (Eastern, North, Northeast, Northwestern, and Southwest), transmission networks of ~2646 km @ 500 kV and ~11,654 km @ 220 kV, 45 installed power plants (26 reservoir-based hydro, 15 natural gas, and 4 coal) totaling ~15,680 MW of installed capacity, and 14 ongoing power generation expansion projects that will represent ~4054 MW of additional capacity. Total electricity demand in Colombia is expected to increase by ~2.82% per year, i.e., from ~64.44 TWh in 2015 to ~91.68 TWh in 2029, and can be represented by a load curve consisting of 2 h/day peak load block and 22 h/day base load block [65,66]. Details regarding the 2015 power generation fleet and electricity demand associated with the Colombian power system are summarized in Table 1. Non-spinning reserve of ~15% of the peak power demand and spinning reserves of ~5% of current electricity demand are required in order to ensure the reliability of the system. In the fossil fuel market in Colombia over the period 2015–2029, coal prices are expected to range between 1.86 $/MM Btu and 4.99 $/MM Btu while natural gas prices will likely vary from 3.97 $/MM Btu to 14.47 $/MM Btu [66]. High gas prices are expected at the end of the time horizon because of the dynamics of the Colombian gas market, including a projected shift from Colombia being a self-sufficient gas supplier to a net gas importer [65]. Additionally, the fossil fuel prices vary not only with the location of each power plant but also with the season of the year. Moreover, under the COP21 pledges [69], the Colombian government has committed to reduce CO_2 emissions and thus it is very likely that the retrofitting of coal power plants with carbon capture and sequestration (CCS) technologies will be required.

In addition to existing transmission network, existing power plants, and ongoing power generation expansion projects, investments in new power plants, carbon management technologies, transmission expansion, which involves both repowering of existing transmission connections and installation of new transmission circuits, will be required in order to meet the growing electricity demand. Announced new power generation projects include the following:

1. Two reservoir-based hydroelectric power plants (500 MW and 800 MW) located in the Northwestern region.
2. Two natural gas power plants of 300 MW and 200 MW located in the Southwest and North regions.
3. Two coal-based power plants of 250 MW and 350 MW located in the Eastern and North regions.
4. Three wind farms (99 MW, 195 MW, and 180 MW) located in the North region.
5. Two geothermal power plants of 100 MW and 275 MW located in the Northeast and Southwest regions.

The capital investment for new power generation projects was based on information from the IEA and the Nuclear Energy Agency (NEA) [70–72] as well as the U.S. Energy Information Administration (EIA) [73]. Operational parameters including emission factors and heat rate were taken from UPME [66] and XM [68]. A capacity factor of 35% was used for the wind farms [70–72]. Availability and capacity factors, for fossil power plants were based on historical operation data obtained from XM [74]. The capital and operation costs, including energy consumption, associated with retrofitting of coal power plants with CCS technologies were obtained from process simulations implemented in Aspen HYSYS® [75] (a commercial process simulator) and Aspen Capital Cost Estimator® [76] (a capital cost estimating tool). The widely used Monoethanolamine (MEA)-based CO_2 absorption process, designed to capture 95% of the CO_2 emissions from a conventional coal power plant, followed by CO_2 dehydration and compression processes were the basis for these cost estimates. Further details are presented in a previous study [65].

2.2. Deterministic power planning framework

The main aspects considered in the mathematical formulation of the deterministic power planning framework, developed by the authors [65], are summarized in Table 2. This model was applied to a variety of case studies in the Colombian context, including the "business as usual" and "CO_2 mitigation policy" scenarios. The reader is referred to the original model publication [65] for more details regarding the model formulation and implementation, e.g., detailed description of the model parameters, variables, and constraints. In summary, the deterministic optimization framework consists of two different components: (i) Input data, consisting of scalars and parameters, such as, capacity, capacity and availability factors, operating cost, capital cost, fuel cost, and emission factors, used to describe the power generation fleet, the transmission network, as well as the energy supply and demand at each region, and (ii) the Deterministic optimization model itself, which is summarized in Table 2. The outcomes of the framework consist of information concerning the optimal primary energy and power generation mix for each time period, allocation of spinning and non-spinning

Table 1
Existing (2015) power generation fleet and electricity demand in the Colombian interconnected power system [66–68].

Region	Hydropower plants		Natural gas plants		Coal power plants		Electricity demand	
	# of units	Total Capacity (MW)	# of units	Total Capacity (MW)	# of units	Total Capacity (MW)	Demand 2015 (TWh)	2015–2029 growth (%)
Eastern	6	3346	–	0	1	225	17.69	23.80
North	1	338	7	2119	1	302	14.61	83.38
Northeast	1	819	3	408.97	2	482	7.03	51.55
Northwestern	10	4769.78	2	738	–	0	9.90	24.82
Southwest	8	1647	3	485	–	0	15.20	31.40

Table 2
Summary of the features of the deterministic power planning framework [65].

Model component	Description
Objective function	The net present value (NPV) of the total cost was chosen as objective function to be minimized. The total cost is composed of the operational expenditures (including transmission cost) and the total cost associated with capital investments for the power system design and operation over the entire time horizon
Operating expenditures	The cost components of operating expenditures are fixed operating cost, variable operating cost, and fuel cost. The fuel cost is a function of the heat rate
Transmission cost	This operational cost refers to the maintenance and operation of transmission assets. It is a function of the unit transmission cost and the electricity flow between regions
Capital expenditures	The capital cost items are associated with investments in already planned and new power plants as well as in transmission capacity expansion, i.e., repowering existing circuits and/or adding new circuits
Primary energy sources	
Natural gas, coal	Fossil energy sources are only available in limited amounts. Thus, the supply of fossil fuels cannot exceed their availability. Primary energy demand for natural gas and coal power plants is a function of their heat rate
Power plants	
Construction and operation	Power generation assets are classified into three categories: existing, already planned, and new (potential) power plants. Already planned power plants, which are either under construction or fully committed, can be operated only after the corresponding expected startup date. Moreover, new (potential) power plants, which could be built or not, can be built only once in the entire planning horizon and can be operated only after the end of the corresponding construction period
Capacity factor	The capacity factor is defined as the ratio between the energy generated during a given time period and the energy that would be generated by the power plant operating at its maximum capacity during that time period. The power allocation, for each time period, cannot surpass the maximum generation capacity of each power plants. This maximum capacity is a function of both the capacity factor and the nominal capacity of the power plant
Availability factor	The availability factor is expressed as the ratio between the amount of time that the power plant is available to produce power over a specified time period and the length of that time period. For each power facility, the dispatch of electricity plus the allocation of spinning reserve should not exceed the maximum amount of electricity that could be produced by that power facility. This maximum amount of electricity is a function of both the availability factor and the load duration curve, represented by load blocks
Reserve constraints	
Reserve margin and spinning reserves	Reserve margin and spinning reserve constraints are included in order to ensure the reliable and safe operation of the electric network in real time. Moreover, reserve margin is applied to guarantee that there is additional power generation capacity over and above the power generation capacity required to meet forecasted peak power demand. Likewise, spinning reserves are used to guarantee the stability of electric network frequency when abrupt load fluctuations and/or emergency operating conditions take place
Power transmission	
Repowering of existing circuits and installation of new circuits	The required transmission capacity expansion can be achieved by repowering existing power transmission lines and/or by adding new circuits between regions. The repowering of transmission lines refers to the transmission capacity expansion by taking advantage of the existing power transmission assets [77]. Kirchoff's current law (KCL) or Kirchoff's first law and Kirchoff's voltage law (KVL) or Kirchoff's second law were formulated based on the direct current approximation and using the Big-M or disjunctive approach [78–80]
Electricity demand	
Electricity demand constraints	The electricity demand in each region can be met either by local generation or by a mix of local generation and electricity import from other regions. Electricity balance constraints for each region are based on Kirchoff's first law, taking into account transmission losses
CCS technologies	
Constraints for CCS retrofitting	The integration of CCS technologies into fossil power plants, particularly those that use coal as primary energy, are considered for the abatement of CO_2 emissions. CCS technologies focus on the post combustion CO_2 capture by absorption using solvents and the subsequently CO_2 dehydration, compression, transportation, and geological sequestration. Different constraints are used to model the reduction in CO_2 emissions from fossil power plants, the reduction in the electricity generation capacity due to electricity that is required for CO_2 management, and an increase in capital and operational expenditures associated with the CCS retrofitting
CO_2 emission constraints	
Emission reduction target	Different constraints are used for the estimation of total CO_2 emissions from fossil power plants as well as to ensure that the reduction target for total CO_2 emissions is achieved

reserves, total electricity generation and transmission cost, as well as optimal investment plan.

2.3. Uncertain parameters

Uncertainties are defined as factors which can affect the performance of a system and cannot be estimated with certainty or are not controlled by the system [81]. Initially, uncertainty in 7 parameters, i.e. electricity demand, natural gas prices, capacity factor of hydropower plants, climate policy or CO_2 emission constraint (based on COP21 pledges), and capital cost (Capex) of wind, geothermal, and CCS technologies, was considered. Uncertainty associated with the power outputs of the wind farms was not considered, since the total capacity of the new wind farms is less than 3% of the total generation capacity of the power systems. Information regarding the uncertainty in electricity demand and natural gas prices was collected from UPME [66]. Additionally, lower and upper bounds for the CO_2 emission reduction target were based on the Colombian COP21 pledge, which are provided by UNFCC [69]. Based on the COP21 pledge, the Colombian government committed to a reduction of 20–30% in greenhouse gas emissions by 2030, from the business as usual scenario. Similarly, lower and upper bounds for Capex of wind and geothermal power plants were based on information from the EIA and the NEA [71–73]. For CCS technologies, a percentage of variation for the Capex estimated previously (in Section 2.1) was defined based on reports from the IEA and the NEA [70–72].

To quantify the capacity factor of hydropower generation in Colombia, historical data was collected from XM [74] for the 2005–2014 time period. Then, the Climatic Research Unit dataset (CRU 3.23) [82] was used to obtain the annual average ambient temperature and precipitation in Colombia for the same time period. Based on the historical data, a quadratic polynomial correlation (shown in Eq. (1)) was developed for the average capacity factor (variable $AvCF_t$, t represents the time period, i.e., year) using the normalized annual

average ambient temperature (variable $AvTe_t$) and precipitation (variable $AvPr_t$) as input variables, as shown in Fig. 2. Although similar simplified modeling approaches have been developed for hydropower plants, e.g., linear model for hydropower generation as function of the runoff [33], more rigorous hydropower models are preferable for improved accuracy. For instance, rigorous hydropower models consider storage dynamics, i.e., reservoir inflow volume, evaporation loss, and water released, as well as the effects of turbine efficiency and hydraulic head on hydropower production [14,28,37]. However, detailed information regarding the reservoir and turbine features for each hydropower plant was not publicly available. Therefore, operating decisions, buffer effect of hydropower reservoirs, and effects of local climate are not included in the model used in this study. Instead, these impacts are aggregated within the hydropower capacity factor for purposes of the optimization model.

$$AvCF_t = 1.053 - 0.6013 * AvTe_t - 0.7935 * AvPr_t + 0.4881 * AvTe_t * AvPr_t + 0.3701 * AvPr_t^2 \quad \forall\ t \tag{1}$$

Then, the four 'representative concentration pathways' (RCPs) [83,84], i.e., RCP2.6, RCP4.5, RCP6.0, and RCP8.5 (details are provided in Table 3 and Fig. 3), were used as climate change scenarios in combination with 18 GCMs (BCC-CSM1-1, BCC-CSM1-1-M, CCSM4, CESM1-CAM5, CSIRO-MK3-6-0, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-R, HADGEM2-AO, HADGEM2-ES, IPSL-CM5A-LR, MIROC-ESM, MIROC-ESM-CHEM, MIROC5, MRI-CGCM3, and NORESM1-M) to forecast the two aforementioned climatic variables for the 2015–2029 time horizon. The RCPs scenarios, which represent four greenhouse gas concentration trajectories, are commonly used by the energy modeling and climate research communities to project global [28,85] and regional [86–88] climate change impacts on energy systems. Moreover, GCMs are mathematical models used to simulate the Earth's natural systems, which involve physical processes in the atmosphere, land surface, cryosphere and ocean [83,89]. These models are used to evaluate how the global climate system responds to changes in greenhouse gas concentrations. The aforementioned 18 GCMs have been used to assess climate change impacts on precipitation over tropical regions [9] and hydropower resources [86]. Here, based on the outcome of the four RCPs and eighteen GCMs, the empirical correlation shown in Eq. (1) was used to forecast the capacity factor of hydropower generation for the four RCPs and for the same time frame. Finally, lower and upper bounds for the capacity factors were generated based on the outcome for the four RCPs, using the multi-model ensemble approach [90,91].

2.4. Global sensitivity analysis

A global sensitivity analysis (GSA) [101–103] (described in Fig. 4) was implemented based on the group sampling approach [104] for parameters that depend on time and/or location, i.e., electricity demand, natural gas prices, capacity factor of hydropower plants, and capital cost (Capex) of wind, geothermal, and CCS technologies. The climate policy or CO_2 emission constraint was considered as just one uncertain parameter. The GSA allows for the quantification of the effect of each individual source of uncertainty on the output of a model [104]. Indeed, GSA has been used to identify the most influential uncertainties involved in the energy modeling for policy support [105] as well as in energy transition pathways [106]. The capacity factor of each hydropower plant, $CF_{h,t}$, was estimated using Eq. (2).

$$CF_{h,t} = \alpha_h * AvCF_t \quad \forall\ h,\ t \tag{2}$$

Parameter α_h is based on historical data for the 2012–2014 time period [74]. The parameter α_h was estimated as the average ratio between the average capacity factor ($AvCF_t$) and the capacity factor of each hydropower plant ($CF_{h,t}$). The index h is used to denote hydropower plants in the power system.

The first step in the GSA (Fig. 4) is to select the set of parameters to be evaluated, i.e., seven in this case, and to assign a given probability distribution function (PDF) for each of them. In this study, the uniform distribution was used for the 7 parameters with the lower and upper bounds discussed in Section 2.2. Although uniform distributions have been used in previous studies to model uncertainties associated with energy and power planning problems [62,107], for detailed subsystem studies more systematic approaches are recommended for the modeling of each uncertainty, e.g., econometric modeling, expert elicitations and vector autoregressive models [52]. Next, the Sobol' sequence sampling method [108], with 258 evaluation points, was used for the assessment of first- (S_i) and second ($S_{i,j}$)-order sensitivity indices. The Sobol' sequence is one of the most effective sampling methods used in GSAs [104]. Finally, for each uncertain parameter i, the total sensitivity index (ST_i) was estimated. The GSA was implemented using the software SobolGSA [109]. First order sensitivity indices (S_i) were estimated using Eq. (3), while second order sensitivity indices ($S_{i,j}$) were calculated using Eq. (4). Indices i, j denote uncertain parameters. The expression $V(E(Z/P_i))$ represents the variance of the expected value of output variable Z given parameter P_i. The term $V(Z)$ represents the total variance of the output variable Z, e.g., total cost associated with the expansion and operation of the power system. The expression $V(E(Z/P_i, P_j))$ represents the variance of the expected value of output variable Z Y given parameters P_i and P_j. The first-order sensitivity index, defined in Eq. (3), denotes the main effect contribution of each

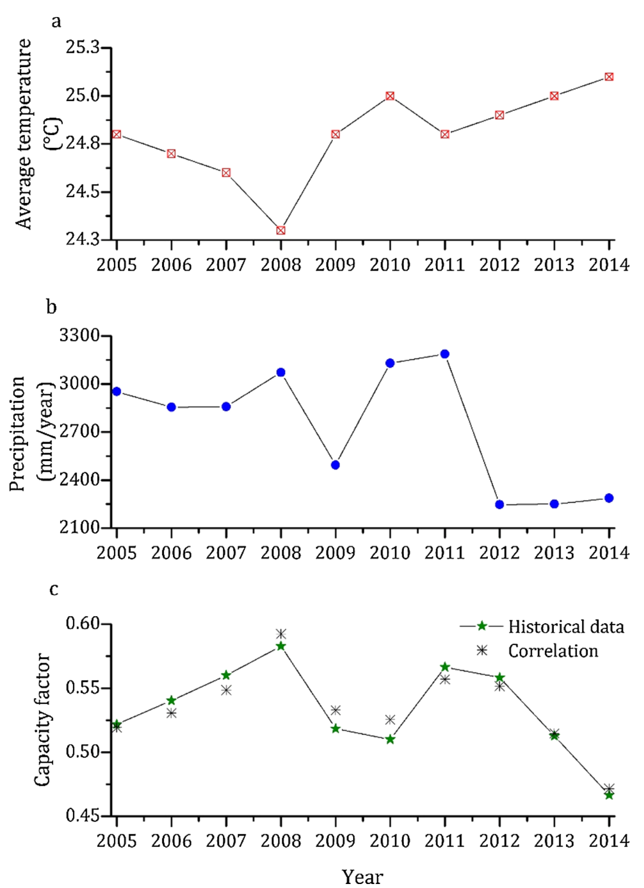

Fig. 2. 2005–2014 average ambient temperature, average precipitation, and capacity factor of hydropower generation in Colombia. a, average annual ambient temperature (red rectangles represent the historical data). b, average annual precipitation (blue circles represent the historical data). c, average capacity factor for hydropower generation (green stars represent the historical data and black asterisks represent the estimated value using a quadratic polynomial function). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
RCPs description and references (IA: Integrated Assessment).

Scenarios	Description	IA Model	Publication-IA Model
RCP8.5	Rising radiative forcing pathway leading to 8.5 W/m^2 in 2100	MESSAGE	[92,93]
RCP6.0	Stabilization without overshoot pathway to 6 W/m^2 at stabilization after 2100	AIM	[94,95]
RCP4.5	Stabilization without overshoot pathway to 4.5 W/m^2 at stabilization after 2100	GCAM (MiniCAM)	[96–98]
RCP2.6	Peak in radiative forcing at ~3 W/m^2 before 2100 and decline	IMAGE	[99,100]

uncertain parameter to the variance of the output variable. The second-order sensitivity index, defined in Eq. (4), represents the joint contribution of a given pair of uncertain parameters on the variance of the output variable.

$$S_i = \frac{V(E(Z/P_i))}{V(Z)} \quad \forall\ i \tag{3}$$

$$S_{i,j} = \frac{V(E(Z/P_i, P_j)) - V(E(Z/P_i)) - V(E(Z/P_j))}{V(Z)} \quad \forall\ i, j \tag{4}$$

Total sensitivity index (ST_i) for each uncertain parameter is estimated as the sum of the first order index and all of the binary interactions involving that parameter (as described in Eq. (5)).

$$ST_i = S_i + \sum_j S_{i,j} \quad \forall\ i \tag{5}$$

2.5. Stochastic optimization framework

The GSA outcome identifies the most influential uncertain parameters in the power planning problem. Based on this reduced set of uncertain parameters and a deterministic optimization model previously developed by the authors [65], a two-stage stochastic optimization framework [60,110] (illustrated in Fig. 5) was implemented. First, the decision variables were divided into first- and second-stage decisions. The first stage variables represent decisions that are made before the realization of the uncertain parameters, while the second stage variables capture decisions that are made after the actual realization of the uncertainties becomes known, as described in Fig. 5 [60,61]. Investments in new power generation and transmission assets were selected as first-stage decisions, while power allocation, non-spinning and spinning reserve allocation, and power transmission flows across the transmission network were considered as the second-stage decisions. Then, a determinist equivalent problem, i.e., a Mixed Integer Linear Programming (MILP) model, was formulated and implemented using the General Algebraic Modeling System (GAMS) [111]. A summary of the main features of the stochastic model, illustrated in Fig. 5, is presented in Table 4.

The solution of stochastic programming problems can be computationally expensive, especially when problems of practical scope are addressed. However, there are simpler approaches that can be implemented to solve optimization problems with uncertainties in the parameters of the model. For instance, a deterministic optimization model can be obtained by fixing the uncertain parameters at their expected values. Another approach consists of solving several deterministic optimization models and combining these particular solutions using heuristic rules [60,110]. However, there is no guarantee that these approaches lead to optimal or near optimal solutions. Indeed, these approaches could be totally inaccurate.

There are two metrics that can be used to evaluate the merits of the approach consisting of modeling uncertainty, solving the stochastic model, and implementing the corresponding optimal solution, namely:

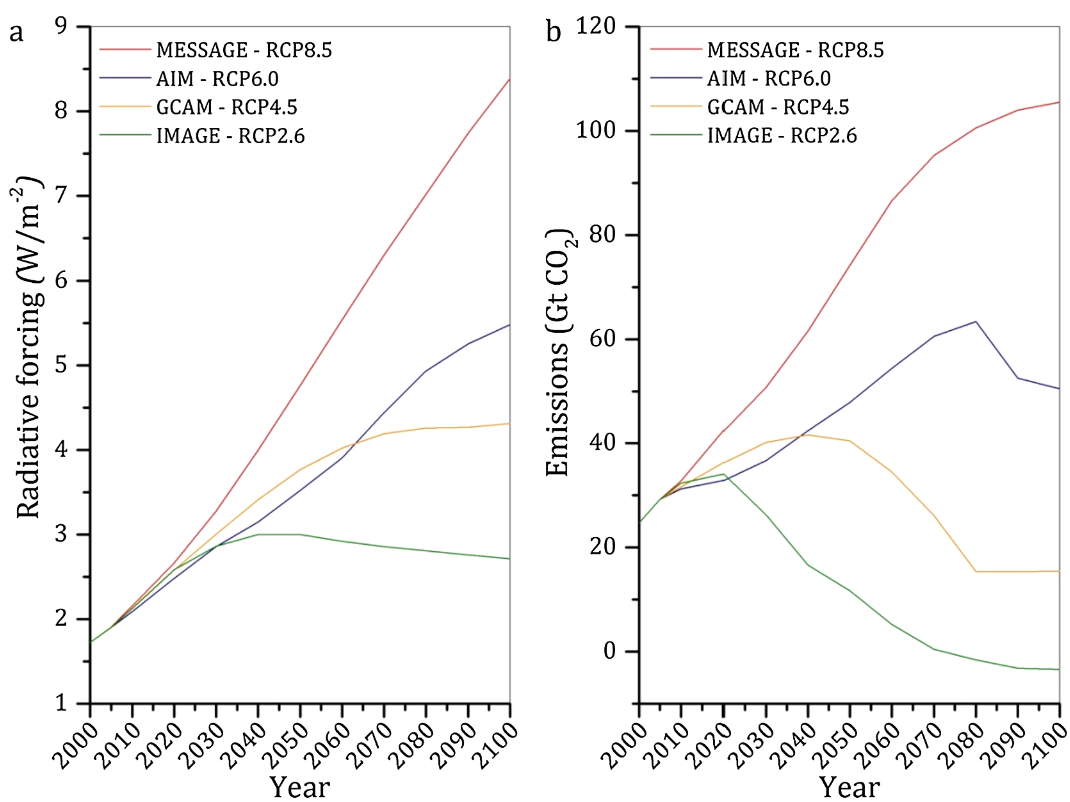

Fig. 3. Representative concentration pathways. a, Radiative forcing relative to pre-industrial levels. b, Industry and Energy CO_2 emissions for each RCP.

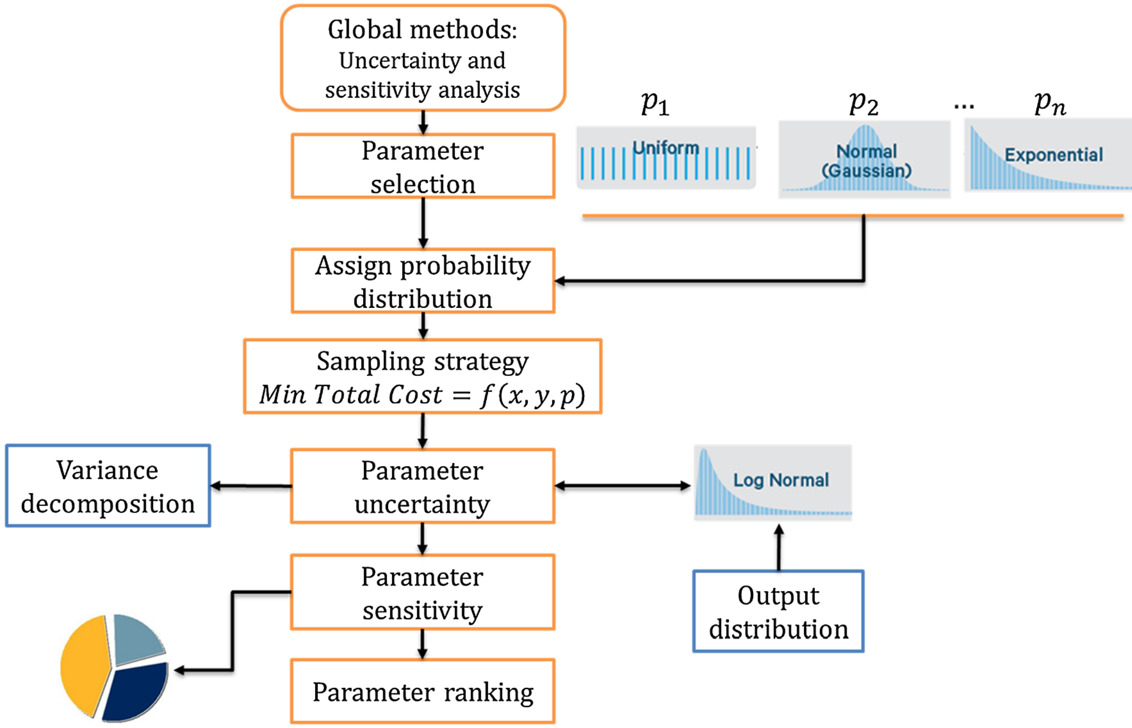

Fig. 4. Schematic for the Global Sensitivity Analysis (based on information from Ref. [103]). Orange squares denote steps of the global sensitivity analysis. Blue squares represent outcomes of the global sensitivity analysis. Solid gray squares denote probability distribution functions associated with uncertain parameters and output variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the expected value of perfect information (EVPI), which measures "*the maximum amount a decision maker would be ready to pay in return for complete (and accurate) information about the future*" [60] and the value of the stochastic solution (VSS), which measures "*the gain obtained from modeling random variables as such, avoiding to replace them with average values*" [61]. The metric EVPI is the difference between the optimal value of the total cost (Z^*) obtained using the stochastic formulation and the value of the total cost (Z^{ws}) obtained from the *wait-and-see* approach (defined in Eq. (6) and illustrated in Fig. 6). On the other hand, the metric VSS is the difference between the expected total cost using the expected value solution (Z^d) and the optimal value of the total cost from the stochastic approach (defined in Eq. (7) and illustrated in Fig. 6). These metrics are particularly useful for the quantification of the expected cost of the uncertainties, i.e., EVPI, and the benefits of

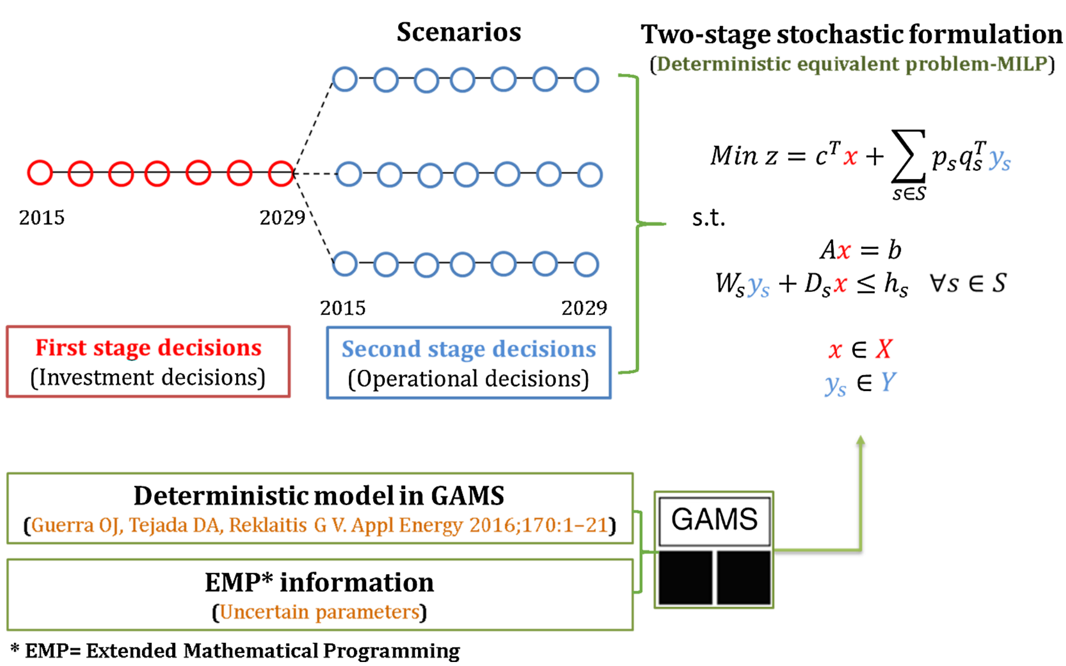

Fig. 5. Two-stage stochastic optimization framework. Red circles represent time periods associated with first stage decisions. Blue circles denote time periods associated with second stage decisions. Red and blue colors are used to denote first stage and second stage variables in the two-stage stochastic formulation, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Summary of the features of the stochastic power planning framework.

Model component	Description
Objective function	The expected net present value (NPV) of the total cost was chosen as objective function to be minimize. The objective function is composed of a deterministic term (associated with the first stage decisions) and the expectation of the second-stage objective. The deterministic term is the NPV of the total capital investment and the second-stage objective is the NPV of the operational expenditures
First stage decisions (here and now decisions)	
First stage variables	The first stage decisions consist of construction of new power plants, installation of new circuits or repowering of existing transmission lines, and CCS retrofitting of fossil power plants
First stage constraints	The first stage constraints are associated with the maximum number of expansions or installations of power generation and transmission assets as well as CCS retrofitting
Second stage decisions (wait-and-see decisions)	
Second stage variables	The second stage decisions are: power allocation, non-spinning and spinning reserve allocation, power flows across the power system, and additional variables associated with the operation of the power system
Second stage constraints	Second stage constraints are associated with supply and demand of primary energy sources and electricity, capacity constraints of power generation and transmission assets, reserve constraints, emission constraints, and additional operational constraints

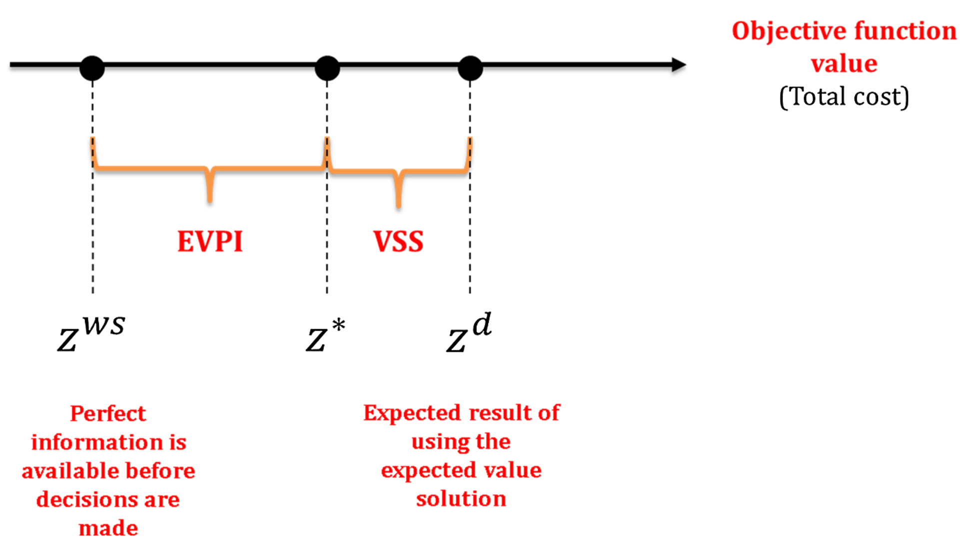

Fig. 6. Value of information and the stochastic solution. The solid black arrow represents the trajectory of the objective function. Solid black circles are used to denote the *wait-and-see*, the optimal stochastic, and the expected value solutions.

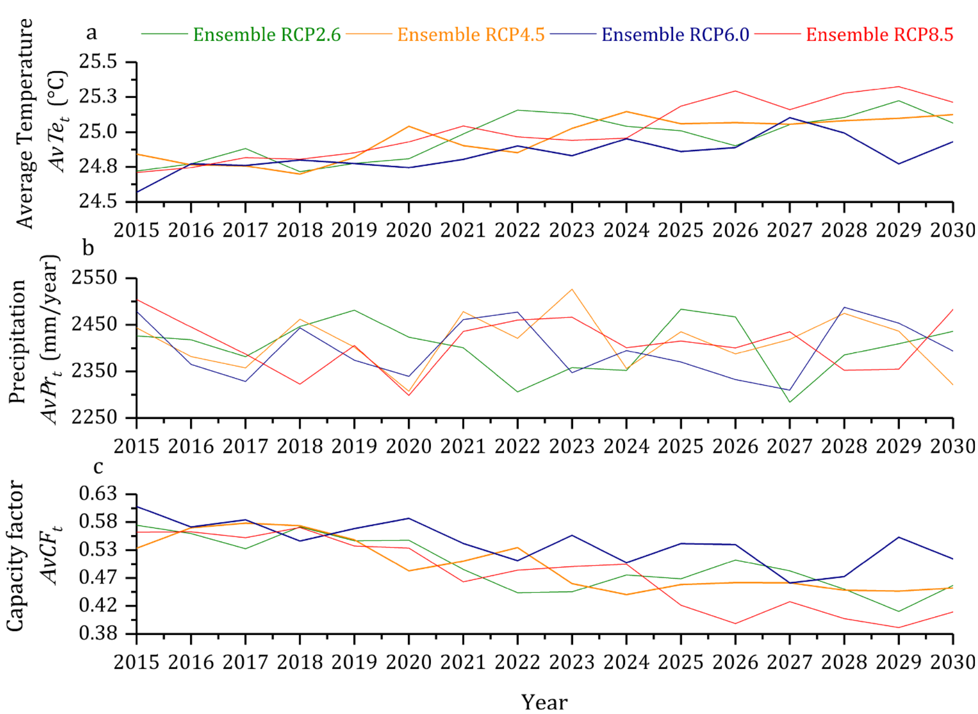

Fig. 7. Projection of climatic variables and capacity factor for hydropower generation. a, projected average annual ambient temperature. b, projected average annual precipitation. c, estimated average capacity factor for hydropower generation (the capacity factor was projected using a quadratic polynomial correlation with average annual ambient temperature and precipitation as input variables, as defined in Eq. (1)).

using the stochastic model for the planning of the power system, i.e., VSS. A relative high value of EVPI would indicate that the uncertainties play an important role in the optimal expansion plan for the power system. Thus, efforts should be directed towards a better quantification and, if possible, reduction of the uncertainties involved in the planning problem. Further, a high value of VSS would indicate that the solution from the stochastic model provides a significant value in comparison with the deterministic solution approach.

$$EVPI = Z^{*} - Z^{ws} \tag{6}$$

$$VSS = Z^{d} - Z^{*} \tag{7}$$

3. Uncertainty quantification and global sensitivity analysis

3.1. Climate change and hydropower generation

It can be expected that climate change will likely affect the capacity factor of hydropower generation, however the extent of such impact is uncertain and thus needs to be quantified. As described previously, the capacity factor for hydropower generation in Colombia can be correlated with the annual average ambient temperature and precipitation, which are two climatic variables very sensitive to climate change. The four RCPs [83,84], i.e., RCP2.6, RCP4.5, RCP6.0, and RCP8.5, were used as climate change scenarios and 18 GCMs were implemented to forecast the two aforementioned climatic variables for the 2015–2029 time horizon (as described in Section 2.3). Note that while similar time horizons have been used in the literature to evaluate the climate change impacts and adaptation strategies for power systems [40,112,113], longer time periods are preferable for these kind of studies [26,114,115], i.e., up to 2100. However, for the 2030–2100 time period, information regarding electricity demand, climate policy, and fuel prices was not available for the power system considered in this study. Every GCM was run individually for each RCP and then the ensemble approach was applied to account for uncertainties in GCM outputs. It is noteworthy that there is significant disagreement among GCM projections of location and direction of rainfall shifts in tropical regions over this century, although large rainfall variations have been consistently projected over a significant portion of tropical land [9].

The results show consistent increases in annual average temperature over the 2015–2029 time period, i.e., increase of 0.50 °C, 0.26 °C, 0.20 °C, and 0.62 °C for RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively (Fig. 7a). Moreover, annual average precipitation is estimated to decline by up to 6% during that time frame (Fig. 7b). Based on these results and using Eq. (1), reductions of 15.4%, 7.7%, 5.5%, and 17.1% in the capacity factor of hydropower generation are projected for RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively (Fig. 7c). For example, for RCP2.6, the capacity factor changes from 0.57 (56.9%) in 2015 to 0.42 (41.5%) in 2029. In summary, climate change is expected to reduce between 5.5% and 17.1% the capacity factor of hydropower generation in Colombia during the 2015–2029 time period. Thus, the Colombia power system is particularly vulnerable to climate change, which translates into uncertainty in the capacity factor of hydropower generation (Fig. 7c). The projected depletion of hydropower resources due to climate change agrees with previous studies that evaluated the impacts of climate change on hydropower sources in South America [113,116].

3.2. Global sensitivity analysis

The extent of the impact of uncertain parameters on the operation, design, and planning of the Colombian power system were evaluated using the deterministic optimization-based power planning framework and the GSA described previously in this manuscript (in Sections 2.2 and 2.4, respectively). Although some uncertain parameters could be correlated, e.g., capacity factor of hydropower plants and climate policy, they were treated as independent inputs during the GSA. Both quantitative and qualitative (summarized in Fig. 8) results were

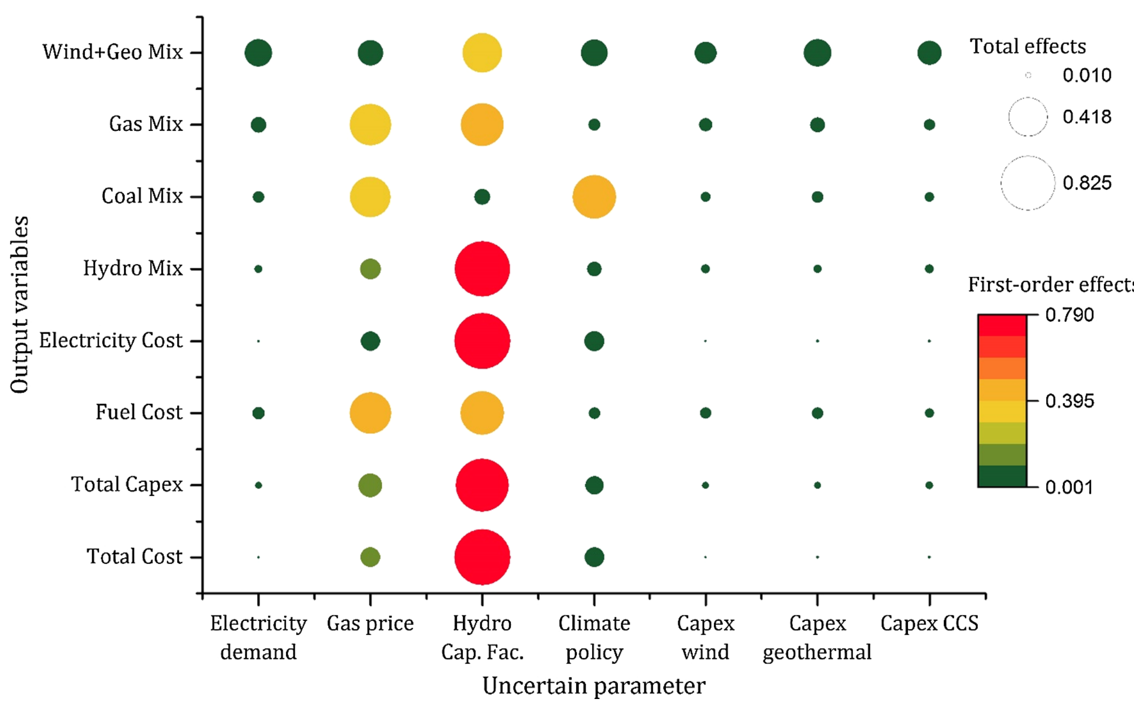

Fig. 8. Global sensitivity analysis for the design and planning of the Colombian power system. The color intensity of the bubbles represents the first order effects (effect of a single parameter on the variance of each model output variable). The size of the bubbles represents the total effects (include the first order effects and all the interactions involving that parameter. Wind + Geo mix: % of wind plus geothermal power generation in the electricity supply mix. Gas Mix: % of generation from gas power plants in the electricity supply mix. Coal Mix: % of power generation from coal power plants in the electricity supply mix. Hydro Mix: % of hydropower generation in the electricity supply mix. The numerical scales associated with the sizes of the bubbles and the colors associated with the bubbles are shown on top right and bottom right of the figure, respectively.

generated from the global sensitivity analysis. The quantitative results indicate that about 79%, 10%, and 7% of the variance of the total cost is due to the individual effect of the uncertainty in the capacity factor of hydropower generation, gas prices, and climate policy, respectively. Thus, ~96% of the variance in the total cost is due to the individual effects of the uncertainty in three parameters, which are the most influential uncertainties in the planning problem (as illustrated in Fig. 8). The individual effect of uncertainty in the capacity factor of hydropower generation also accounts for about 73.2%, 79.0%, and 78.9% of the variance of total capital investment, electricity cost, and the share of hydropower generation in the electricity supply mix, respectively. Similarly, the individual effect of uncertainty in gas price and climate policy accounts for 39.8% and 46.0% of the variance of total fuel cost and the share of coal power generation in the energy mix, respectively. It is noteworthy that the uncertainties in climate policy and gas prices have significant impacts on the share of coal in the energy supply mix, while effects of uncertainties associated with the capacity factor of hydropower plants are minor.

4. Stochastic optimization model

4.1. Model implementation

Based on the GSA, a two-stage stochastic optimization model [60,110] was developed (described in Section 2.5) wherein the capacity factor of hydropower generation, gas prices, and the climate policy are considered uncertain. It is noteworthy that, based on the GSA, the set of uncertain parameters for the development of the stochastic model is reduced from seven to three parameters, which reduces the computational burden while maintaining reasonable model accuracy. The results from the GSA are in line with those reported in previous studies where natural gas prices [52], climate policy [52], and hydropower generation [38] were identified as critical uncertainties in the planning of power systems. The decision variables were separated into two sets; namely, first- and second-stage decision variables, as described in Section 2.5. First-stage decision variables are associated with decisions that must be taken upon before the realization of the uncertain parameters. Once the uncertain parameters have unfolded, recourse or second-stage decisions are made to compensate for the effects associated with the implementation of the first-stage decisions. Two metrics, i.e., EVP and VSS [60,61], are used to assess the impact of modeling uncertainty and using the stochastic programming model in power system planning problems (as described in Section 2.5).

Both deterministic and stochastic formulations were implemented, using a 1 year time step over the 2015–2029 time horizon. The stochastic formulation considers 27 scenarios, which correspond to the combination of the three uncertain parameters, i.e., natural gas price, capacity factor of hydropower plants, and CO_2 emission reduction target, with 3 levels each (low, medium, and high). These scenarios are used to approximate the multivariate stochastic processes associated with the uncertain parameters. The probability associated with each scenario was set to 1/27, since there is no bias regarding the realization of any of these scenarios. A more accurate approach would consist of using continuous probability distributions of these variables to represent the uncertainty space. However, with few exceptions, this more rigorous approach is prohibitively expensive from a computational and practical viewpoint [50]. A summary of the model statistics for both the deterministic and the stochastic models is presented in Table 5. All of the corresponding MILP optimization models were implemented using GAMS 24.4.1 and solved using CPLEX 12.6.1 on a Dell OptiPlex 7010 with Intel® Core™ i7-3770 CPU @3.40 GHz and 16 GB RAM running the Windows 7® Enterprise (64-bit operating system). The relative gap (in GAMS notation OPTCR) was fixed at 1% for all of the cases.

4.2. Deterministic and stochastic expansion plans

The results expressed in terms of the total cost are summarized in Fig. 9. These results indicate that a total expected cost of ~$22.4 billion would be incurred for the expansion and operation of the Colombian power system if uncertainty is not considered during the design and planning of such system, i.e., using expected values for all uncertain parameter and solving the corresponding deterministic optimization problem. Investment expenses will represent roughly 43.3% of the total expected cost, while operational expenditures will account for the remaining 56.7% (Fig. 10a). Investments in hydropower plants will represent ~68.0% of the total required investment. Moreover, investment in fossil, i.e., gas, coal, and CCS technologies, and renewable, i.e., wind and geothermal, power generation will represent about 18.1% and 11.0% of the total expected investment (Fig. 10a). However, if uncertainty is taken into account, the total cost will rise to ~$24.6 billion (an increase of ~10%), while investments will increase to $10.64 billion (an increase of ~9.8%), as shown in Figs. 9 and 10b. It is noteworthy that investments in hydropower plants and transmission assets would be reduced, while capital expenditures in fossil power generation, carbon management technologies, and renewable power plants would be increased. The variations in the investments in hydro, natural gas, and renewable power plants are due mainly to the rescheduling of capital investments, while the variations in the capital expenditures in coal power plants, CCS retrofitting, and transmission assets are due both to the rescheduling of capital investments and to the investments/divestment in new assets. For instance, the number of coal power plants retrofitted with CCS technologies increases by more than one-fold when the stochastic solution is compared with the deterministic solution. Regarding transmission expansion, the drop in the capital investment is mostly driven by a reduction in the expansion of transmission capacity between the region with the highest share of hydropower generation, i.e., the Northwestern region, and others interconnected regions. The Northwestern region account for roughly 35.1% of the total installed generation capacity in the Colombia power system and hydropower plants represent a share of ~86.6% of its total installed generation capacity [65]. Thus, for the Colombian power system, the uncertainty in hydropower resources has a direct impact on the transmission expansion plan.

Regarding the impacts of modeling the uncertainties and implementing the stochastic solution approach, the metrics EVPI and VSS were estimated to be ~4.5% and ~5.7% of the total expected cost. This indicates that both the modeling of uncertainty and the implementation of the stochastic solution are critical in the rational design and planning of the power system. Indeed, the value of the EVPI metric provides an estimate of the scale of the maximum investments that could justifiably be used in projects associated with the modeling of the uncertainties in the aforementioned power system, while the value of VSS gives an estimate of the maximum investments that could be used in the development of stochastic decision-support tools for the design and planning of the power system.

5. Conclusions and policy implications

From a policy perspective, the results from this study indicate that

Table 5
Model statistics: 27 scenarios, 3 uncertain parameters, and 3 levels each.

Model statistics	Deterministic	Stochastic (SP)
Total number of variables	11,656	298,342
Continuous variables	10,036	269,377
Binary variables	1,620	28,965
Total number of constraints	7,976	211,037
Non zero constraint matrix elements	68,075	1,797,358
CPU time	4.6 s	10.9 min

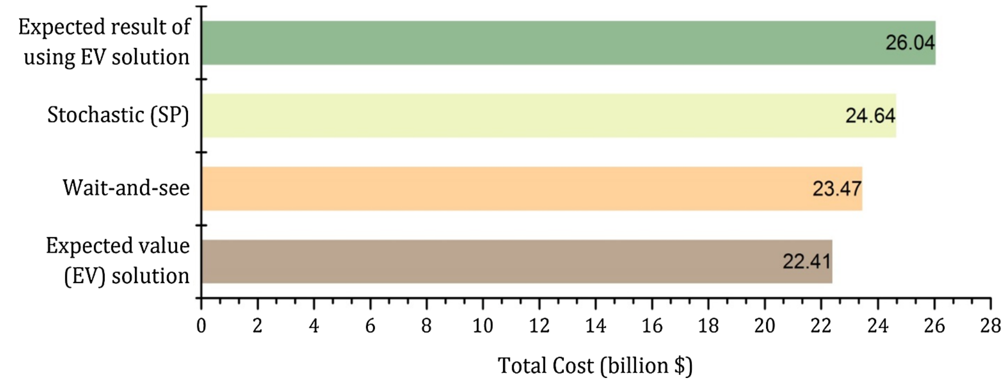

Fig. 9. Summary of optimal solutions for deterministic and stochastic solution approaches. Horizontal bars represent the numerical values associated of the optimal solution of the solution approaches reported in the vertical axis.

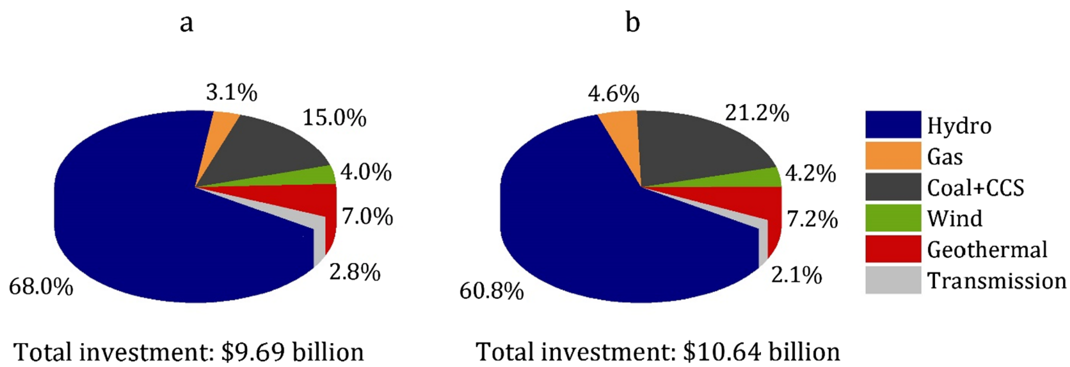

Fig. 10. Comparison of deterministic and stochastic solutions of the design and planning of the Colombian power system. a, total cost breakdown for the deterministic solution. b, total cost breakdown for the stochastic solution.

hydropower generation may not be a cost-competitive alternative to mitigate carbon emissions in Colombia. By contrast, it seems that the deployment of wind power resources in the North region and the implementation of carbon capture and sequestration technologies in coal power plants in the Northeast region are key for both the reduction of carbon emissions and the adaptation to climate change. Indeed, the electricity demand growth in Colombia is expected to be driven mostly by the North region, which is expected to face an increase in electricity demand of ~83.4% over the 2015–2029 time horizon [65]. Moreover, this region is a net electricity importer and has one of the highest potentials for wind power generation in Colombia. However, more policy and regulatory efforts are needed for the large-scale deployment of variable renewable energies in Colombia. Additionally, as illustrated by the global sensitivity analysis (illustrated in Fig. 8), the variability (due to climate change) in the share of hydropower generation in the energy mix is compensated by shifting to the generation from natural gas power plants instead of from coal-based power generation. This is mainly because the coal-based power generation is driven by the emission reduction policy. This situation raises concerns regarding Colombian national energy security. For instance, climate change will increase the demand of natural gas in the power sector but Colombia could face a natural gas supply transition from being self-sufficient to becoming a net importer in the next three or four years [65,117,118]. Therefore, policy and regulatory efforts are required in order to increase the domestic natural gas supply via the exploitation of off-shore natural gas and/or shale gas resources. From an operational viewpoint, the reduction in the hydropower generation capacity and the large-scale expansion of variable renewable energies (mostly wind in the Colombian case) would require a more frequent dispatch of thermal power plants (natural gas in particular) for the safe and reliable operation of the power system [119,120]. However, this situation could be alleviated by the seasonal complementarity of hydro and wind power [121–123], which occurs in the Colombian power system even during abnormal weather patterns [124,125]. In the literature, there are more cases of complementarity of two renewable energy sources that have been reported, including hydro and solar power [126] as well as solar and wind power [127]. Although the results regarding the role of carbon capture and sequestration technologies in the future Colombian power system are consistent with other studies [40,113,116], there are techno-economic and policy-related issues that must be overcome in order to realize its potential [128,129]. Thus, it seems that the Colombia government should focus more on the policy support for the large-scale deployment of variable renewable energies, especially in the North region. Indeed, variable renewable energies are carbon emission free sources while fossil power plants (even with carbon capture and sequestration) are important drivers of climate change. Further, the main limitations of this study are associated with the model of hydropower plants and the length of the planning horizon. First, a more rigorous model of the hydropower plants considering reservoir inflow volume, water released, hydraulic head, turbine efficiency, and evaporation loss would provide a more reliable quantification of the impacts of climate change on hydropower generation. Second, a longer evaluation period, e.g., 50–100 years, would better reflect the effects of climate change and the corresponding projections of impacts and adaptation strategies will be more valuable for energy policy recommendation and implementation. Thus, future work should be focused on addressing these two limitations.

Power system adaptation to climate change and to announced climate pledges is a very critical issue for an economy. This study illustrates how an integrated model-based system analysis can provide some insights on the optimal adaptation strategies required to meet CO_2 emission reduction commitments for the power sector, to mitigate the impacts of climate change on the operation of a power system, and to deal with the uncertainties inherent to this planning problem.

Specifically, the results presented in this study show that: (1), climate change would likely reduce the capacity factor of hydropower generation, i.e., between 5.5% and 17.1%, in Colombia during the 2015–2029 time period, and (2) the capacity factor of hydropower generation, gas prices, and climate policy (CO_2 emission reduction target) are the most critical uncertain parameters presented in the long-term planning problem associated with the hydro-dominated Colombian power system, e.g., these uncertainties account for ∼96% of the variance in the total cost for the required expansion and operation of the power system, and 3) uncertainties in hydropower generation, gas prices, and climate policy are expected to lead to an increase of ∼10% (∼$2.23 billion) in the total cost required for the expansion and operation of the Colombian power system during the 2015–2029 time frame. This increase in the total expected cost is driven partially by additional investment in gas and coal power plants as well as in retrofitting of coal power plants with carbon capture and sequestration technologies. Even though this study considers only climate change adaptation options at the strategic planning level, alternatives at the power system operation level, e.g., replacement of cooling system types, increased plant efficiencies, and fuel switches, can also be readily accommodated within the framework presented here.

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